Assessing the socio-demographic, technical, economic and behavioral factors of Nordic electric vehicle adoption and the influence of vehicle-to-grid preferences

Article (Accepted Version)

Assessing the Socio-demographic, Technical, Economic and Behavioral Factors of Nordic Electric Vehicle Adoption and the Influence of Vehicle-to-Grid Preferences

Chien-fei Chen*[1], Gerardo Zarazua de Rubens[2], Lance Noel[3], Johannes Kester,[4] Benjamin K. Sovacool[5]

[1]* Chien-fei Chen is an environmental sociologist and research associate professor at the Center for Ultra-wide-area Resilient Electrical Energy Transmission Networks (CURENT), University of Tennessee, U.S.A. Her research examines the social and technological integration, energy justice and renewable energy adoption behaviors; cchen26@utk.edu.

[2]Gerardo Zarazua de Rubens is an assistant professor at the Center for Energy Technologies, Department of Business Development and Technology, Aarhus University, Denmark; His research focuses on energy and transport systems, data analytics and business development and his recent focus Electric Vehicle and Vehicle-to-Grid implementation in Europe. gerardo.zarazua@btech.au.dk.

[3]Lance Noel is a postdoctoral researcher at Aarhus University, Denmark, where he is the lead researcher on a $1.6 million grant on the sociotechnical benefits and barriers of electric vehicles and vehicle-to-grid in the Nordic region; lnoel@btech.au.dk.

[4]Johannes Kester is a senior researcher at TSU, University of Oxford, but at the time of writing a postdoctoral researcher at Aarhus University, Denmark, working on sociotechnical transformations in electricity and alternative transport systems, and the role of security in these transformations. johannes.kester@ouce.ox.ac.uk.

[5]Benjamin K. Sovacool is a professor of energy policy at the School of Business, Management, and Economics, University of Sussex, UK. He is also Director of the Center for Energy Technologies and Professor of Business and Social Sciences in the Department of Business Development and Technology at Aarhus University in Denmark; B.Sovacool@sussex.ac.uk.

Corresponding Author*: Chien-fei Chen**,** Center for Ultra-wide-area Resilient Electrical Energy Transmission Networks (CURENT), Department of Electrical Engineering and Computer Science, University of Tennessee, 508 Min H. Kao Building, 1520 Middle Dr. Knoxville, TN 37996, U.S.A.; cchen26@utk.edu.

Assessing the Socio-demographic, Technical, Economic and Behavioral Factors of Nordic Electric Vehicle Adoption and the Influence of Vehicle-to-Grid Preferences

Abstract

This study investigates the interconnected influence of socio-demographics, behavioral, economic, and technical factors associated with electric vehicle (EV) adoption interest and the influence of vehicle-to-grid mobility on preferences. Using hierarchical regression analysis, we examine the impacts of six dimensions relating to socio-demographic, technical, economic, and behavioral factors in a survey (n=4885) across the countries of Denmark, Finland, Iceland, Norway, and Sweden. Our results show that younger males, with higher income, a higher number of children, and who had experiences with EVs and generally hold sustainability values are positively related to potential EV adoption. Among electric mobility attributes, vehicle-to-grid capability and charging time are determined to be the influential predictors. Adding vehicle-to-grid capability can foster EV adoption in our analysis, considering it can add a revenue stream for EV owners. Individuals continue to use specific knowledge of conventional fuel vehicles when considering EVs and their attributes. Among all of our factors, the fuel economy and financial savings, and environmental value were the strongest predictors. In comparison, the driving range was ranked less critical to former EV owners than a conventional car and current EV owners. Battery life was ranked more important to conventional fuel vehicle owners than current and former EV owners. Finally, former EV owners considered vehicle-to-grid to be more important than current EV and conventional car owners, implying that vehicle-to-grid could be the marginal incentive that would be the "tipping point."

***Keywords*:** electric vehicle; vehicle-grid integration; vehicle-to-grid, diffusion of innovations; low-carbon mobility; electrification of transport

1. Introduction

Electric vehicles (EVs) continue to penetrate national vehicle fleets, having surpassed globally 5.1 million EVs on the road by the end of 2018 [1], [2]. This global stock is mostly concentrated in three areas, with about 45% in China, followed by Europe with 24% and the United States (US) with 22% of the total EV stock. Moreover, in terms of entire vehicle stock, European countries continue to lead the way with Norway having over 10% of all vehicles being either battery electric vehicles (BEVs) or plug-in hybrids (PHEVs), followed by Iceland (3.3%), the Netherlands (1.9%), Sweden (1.6%) and China (1.1%) [1]–[3]. However, China holds the largest vehicle market, with 1.1 million EVs added to its national fleet by the end of 2018 [2].

In terms of the market share of new vehicle sales, EVs continue to progress, particularly in Europe, where countries like Norway, around one of every two sold cars, are electric (see Figure 1). While BEVs accounts for about 64% of the global EV fleet [2], there is a trend within some EVs markets that sees PHEVs becoming the dominant EV option, particularly in countries like Iceland, Sweden, and Finland where over 80% of EVs are PHEVs, and other markets such as Japan and the United Kingdom with around 70% of the EV stock being PHEVs [2]. This trend is due to their ability to mitigate social and industrial barriers of full-electric vehicles such as range anxiety and diminished business revenues, considering PHEVs at their core still have a combustion engine powertrain. Moreover, PHEVs enable continued use of petrol (gasoline) as fuel provides a source of revenue for automakers and their supporting (refueling) networks [4]. Despite the progress of EVs in penetrating some national fleets and increased rates of EV sales, the total stock of EVs remains only at around 0.2-0.3% of the whole global passenger fleet [1], [5]. International Energy Agency projects an entire EV stock of 13 million electric vehicles by 2020, and nearly 130 million by 2030 [1]. In this projection, EV sales increase from 4 million in 2020 up to 21.5 million by the end of the decade, driven by many of the active policies shown in Table 1.

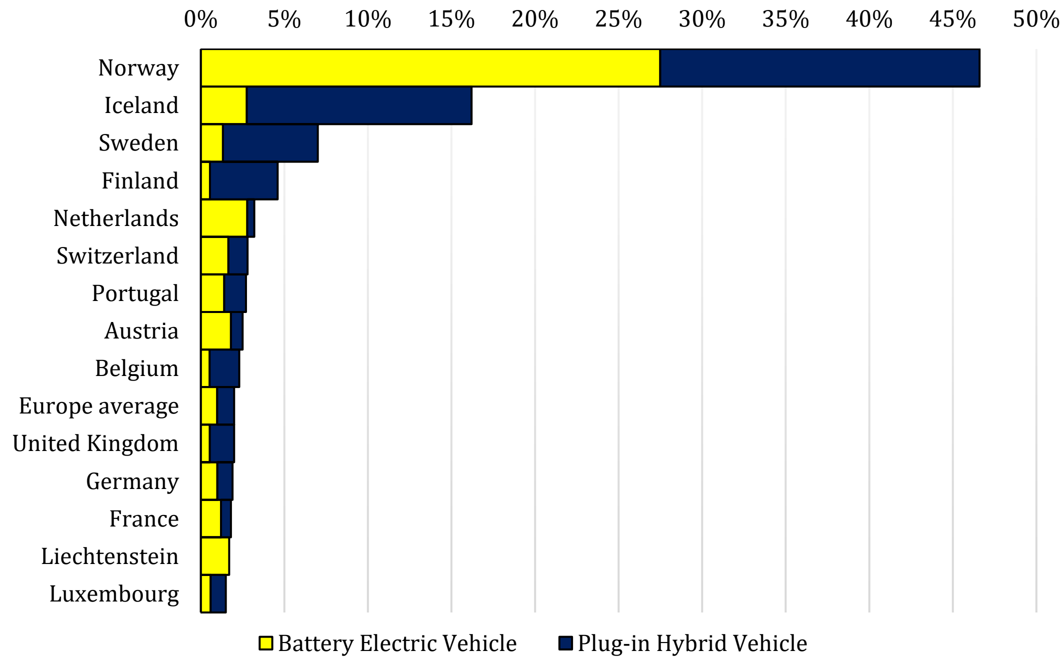

Fig. 1: European electric vehicle market share (new vehicle sales) in 2018.
Data obtained from European Alternative Fuel Association [3]

Table 1
International EV targets for 2020 or 2030

Country or region EV	EV target or objective
China	5 million EVs by 2020 and 40-50% EV sales by 2030
Finland	250,000 EVs by 2030
France	Under revision
India	30% EV sales by 2030
Ireland	500,000 EVs and 100% EV sales by 2030
Japan	20-30% EV sales by 2030
Netherlands	10% EV sales by 2020
New Zealand	64,000 EVs by 2021
Norway	100% EV sales by 2025
Korea	200,000 EVs by 2020
Slovenia	100% EV sales by 2030
United Kingdom	396,000 to 431,000 EVs by 2020
United States (some States)	3,300,000 EVs across eight states by 2025

Note: The list does not include countries such as Sweden and Mexico, as numbers are not disclosed. **Source**: Adapted from International EV Outlook (2018 and 2019) [1], [2].

A significant number of studies have analyzed the independent influence of EV costs, socio-demographics, driving practices, social norms, adoption motivation, the connection between EV acceptance and other sustainable behaviors, and electric mobility factors such as battery life, fuel economy, charging time, charging station availability (among other factors). Nonetheless, less is known about the influence of these interconnected factors together on EV adoption, as well as the link between vehicle-to-grid (V2G) capability and EV adoption intention.

1.1 The Present Study

This study investigates the interconnected influence of socio-demographics, behavioral, economic, and technical factors on EV adoption interest in the Nordic countries, as well as how preferences differ according to V2G capability. Particularly, we draw from empirical survey data and a hierarchical regression analysis (among others) to examine the impacts of a wide range of interconnected factors: socio-demographics (e.g., income, gender, age, etc.), behavioral factors including mobility practices, environmental values and sustainable behaviors (e.g., install energy efficiency appliances, solar panels or renewable energy system adoption, recycling and eat less meat), economic factors or financial attributes, including the expected costs of the next vehicle, vehicle purchase intention and purchase time frame, technical factors of conventional (gasoline) vehicle performance and electric mobility on EV adoption interest.

We defined EVs here as any passenger vehicle that uses energy drawn from the electric grid and stores it on board for propulsion [6]. Our definition thus includes battery electric vehicles (BEVs) and plug-in electric hybrid vehicles (PHEVs), but not other low-carbon options such as e-bikes or those relying on biofuel or hydrogen exclusively, nor conventional hybrid vehicles; as these latter vehicles are mostly run with petrol and diesel. Although motivations and barriers for BEVs and PHEVs may differ, we have treated them as a single class of “EVs” because that is often how they are discussed in the popular press and marketing materials. V2G is defined as the technology that allows EV owners not only to charge an EV, but it also lets people store electricity in its battery and return it back to the electricity grid when the vehicle is connected at home, work or public charging station [7]–[9]. While there is increasing literature on the effects of V2G on the grid and even connecting EVs to virtually "anything" (through V2X) [7], [10], [11], the link between V2G capability and EV adoption remains arguably underexplored.

In proceeding as such, we aim to make three contributions. First, much research focuses on only one dimension to EV adoption, such as driving range or purchase price. Here, we focus on them all, drawing from separate streams of research correlated with six distinct dimensions (socio-demographics, conventional car performance, electric mobility, financial attributes of cost and purchasing intention, mobility practices, and sustainability values). Second, we analyze these six dimensions step-by-step and as well as considering each independent variable's (IV) effect by controlling for other factors' effects. Third, this study is one of the few studies in examining the role of V2G capability in EV adoption interest.

2. Synthesizing Six Dimensions of EV Adoption Interest and V2G Influence

The ever-growing literature on EV and (to a lesser degree) V2G adoption tends to emphasize the importance of six dimensions, transcending different aspects of adopters, conventional vehicle performance, and supporting technological (and social) infrastructure. Below we explore these dimensions.

2.1 Socio-demographics

The first stream of research discusses the salience of socio-demographics and attributes such as gender, education, occupation, or age in mediating preferences or purchasing intentions. As Sovacool et al. [12] write, "The influence of demographics on decarbonizing transport—reflected in preferences for conventional forms of mobility as well as electric vehicles and V2G—is important and complex." Seemingly irrespective of geography, early EV adopters have been identified as individuals who are typically males, of high earning income, middle-aged, with high levels of education, and who can be environmentally and, more importantly, technologically inclined across a variety of studies [13]–[15].

In particular, studies in the Nordic countries have shown that more than half of early adopters showcase a yearly earning income of $60,000 or higher [16], with 20% of this group of individuals reaching incomes of €100,000 or above [17]; whereas in North America over 60% of early EV adopters showed earning incomes higher than $90,000 [14]. This situation is perhaps not a surprise considering the to-date high price positioning of EVs with even entry-level models such as the Nissan Leaf priced ~$35,000 in Europe [18], or between $22-29,000 in the U.S. (depending on tax credits) [19]. However, studies also indicate income level to not be significant, with the caveat that it is younger individuals who tend to express the most EV interest, and these groups have not reached their peak earning years [20].

Regarding gender, more women similarly value the environmental benefits of electric vehicles compared to men in Sweden [16]. However, Yang et al. [21] found that gender was a limited explanatory factor in explaining preferences for new EVs in China. In Norway, the drivers of EVs tend to have higher education than non-adopters, and they report being "highly motivated" by environmental issues (alongside issues of cost) [22]. Another study in Sweden further notes that those in the conventional automobile industry, in particular, will tend to strongly prefer ordinary cars and resist EVs for reasons of reduced after-sales revenue [23]. Büchs et al. [24] write that household size has a more substantial effect on transport emissions (more than other household-related energy emissions). They find that two adult households have almost three times higher transport carbon emissions than single adult households, and also that two adult households with one child have a "significantly higher total." Therefore, EV adoption appears to be influenced by socio-economic factors considering current EV owners tend to have a higher socio-economic status to afford the higher capital investments of an EV.

2.2. Financial Attributes

This category encompasses the traditional economic factors influencing adoption interest, including expected costs, intention to buy a new vehicle, the timing of purchase plans in the next five years. Many authors suggest that vehicles, in general, or EVs in particular, have perceived economic or utilitarian benefits still rooted in more conventional, or functional, decision considerations by users to get from point A to point B [25], [26]. Separating the factors affecting EV adoption into "internal" and "external" categories, some researchers suggest that internal factors include battery costs, purchase price, driving range, and charging time [27]. These typically result in negative attitudes toward a desire to adopt EVs, as these usually have high purchase prices, limited driving range, and long charging times. For instance, the purchase price of EVs is substantially more than other cars [28]. When put in the context of V2G, studies extend this logic by noting there could be sound monetary or financial motivations for adopting EVs, as they can become sources of income by providing energy storage or grid services [29], [30]. Finally, consumer studies have noted, in a sample of 23,000 international surveyed consumers (under 40 y/o), that ~88% of these consumers expect to purchase a vehicle within a 5-year time frame [31].

Admittedly, in the Nordic region, the financial attributes of EVs are strongly driven by national policies[4], [32]. Table 2 shows three sets of interrelated policies that all shape the cost of EVs as well as likely consumer preferences. Transport policies aim to reduce the carbon intensity of passenger transport. Passenger car taxation seeks to level the playing field between EVs and conventional cars, and direct incentives seek to stimulate the attractiveness of EVs further.

Table 2: Transport, tax, and electric vehicle policies in the five Nordic Countries

	Iceland	Sweden	Denmark	Finland	Norway
Transport focused climate targets	2020: 10% RES share in transport. 2050: 50-70% reduction in GHG (comp. to 1990 levels)	2030: 63% reduction in GHG (to 1990 levels). 2040: 75% reduction in GHG (to 1990 levels). 2045: complete carbon neutrality (=	2020: 20% reduction in GHG (comp. to 1990 levels) in non-ETS sector (incl. transport), and 40% in the ETS sector. 2030: 50% renewable energy	2030: Reduce transport GHG emissions by +- 50% (compared to 2005). First replacing current fuels (with biofuels), then alternative technologies and	2025: No new traffic growth in cities and all new passenger vehicles Zero-Emission 2030: over 50% of heavy/commercial transport zero-emission and 50% reduction of GHG emissions (Oslo = 95%)

		85% reduction in GHG to 1990 levels). Transport: 70% reduction by 2030 compared to 2010.	2050: complete carbon neutrality.	services, targeting 250.000 PEVs / 50.000 gas-fueled vehicles. 2050: 80-95% reduction in GHG (compared to 1990).	2050: 100% reduction
Passenger car taxation	Excise duty and weight differentiated registration tax. Annual ownership tax based on weight	Primarily CO2 and weight differentiated yearly ownership tax (no registration tax)	Primarily one-time value-added registration tax Annual ownership tax based on fuel consumption	Annual vehicle tax based on CO2 emissions and weight	Registration tax based on weight, engine and emissions. Fixed annual ownership tax.
EV incentives	Purchase, VAT, annual ownership tax exemptions Support for charging infrastructure	Subsidy on new BEV (4000e) and PHEV (2000e) Company car reduction Five year exemption of annual ownership tax Bonus-malus system (mid-2018)	20% purchase tax until 5000 cars or 2019 (revising the phase out of tax exemptions (up at 40%) Differentiated parking. Tax rebates for chargers	EVs pay minimal technical purchase tax and ownership tax, no other special arrangements. As of Jan 2017 5 mln for chargers	Purchase tax and VAT exemptions; 50% company car tax Since 2015 local authorities decide on pricing level of PEV parking, toll roads, ferries and HOV lanes (max 50% of highest price). Infrastructure support on national and local level.

Source: modified from[32]

2.3. Mobility Practices

This category captures behavioral factors such as mobility practices, number of cars in the household, driving distances, driving regularly, year of having a driver's license, and former experience with an EV. Studies suggest that there are interconnected relationships among the number of cars, income, and driving distances, and driving range. For example, multi-car households tend to have higher income [33], [34], and are thus more likely to afford the higher price of BEVs. Higher income is also correlated to higher annual mileage and could imply more trips that exceed the electric driving range of a BEV, indicating the chance that the BEV is replaced by either a conventional vehicle, or by renting another vehicle [35]. Thus, considering the driving needs of consumers is a necessary factor for a systemic understanding of the early BEV adoption in multi-car households.

Moreover, experiences with a particular form of transport can strongly link to positive (or negative) attitudes about it. Abenoza et al. [36] found that the longer one traveled on public transport in Sweden, the lower their satisfaction with it. Similarly, Ensslen et al. [37] and Larsen et al. [38] both found that experiences with EVs, or exposure to them, meaningfully increased positive attitudes and the likelihood to purchase one. There is even an emerging body of research, which suggests that EV adoption is shaped by a "learning by driving" process of experiential acceptance where one of more signficiant predictors towards driving an EV is actual on-the-road, visceral experience with it [39], [40]. Over time, the practice of driving an EV solidifies into a stronger affinity and identity as a particular type of user and it also reflects a higher degree of competence and consciousness. Knowledge about EVs, in other words, is strongly gleaned through using them [41], [42], which can create momentum towards further reinforcing behavior.

2.4 Conventional Vehicle Attributes

The literature suggests that technical factors that have traditionally been associated with conventional fossil fuel vehicle's attributes, including ease of operation, speed, or fuel economy, will influence actual or potential vehicle purchases (independent of demographics). For example, a recent study that aimed to identify the vehicle attributes consumers value before and after a purchase, notes that the design and looks of a car (interior and exterior design), its cost (purchase price, costs of ownership or cost savings), practicality and comfort, ease of operation, and technical reliability were among the most influential factors affecting consumers [43]. Others note that beyond price, factors like fuel consumption (economy), technical quality (reliability), vehicle style (glances) and acceleration drive vehicle purchases [44]. The importance of the style and design (looks) of vehicles in influencing purchasing decisions, is also noted more predominately by industry-based studies [45]; however, the importance of such attribute erodes post-purchase [43]. While the literature may differ in agreeing on the exact combination of vehicle attributes that act as the primary determinant of vehicle purchases [43], scholars suggested that consumers looking into different vehicle technologies often do consider performance and its attributes as critically salient [46].

2.5 Electric Mobility

Electric mobility encompasses the uniquely electrical aspects of an EV, such as charging availability, range, and battery life. Many studies mention the necessity of easily accessible and/or cheap or free charging infrastructure along with competitive (or free) tariffs and improvements in battery range as vital to the adoption of EVs [47]–[49]. The notion of "range anxiety," specific to electric mobility, has emerged to reflect the problem of EV drivers developing negative psychological feelings of anxiousness when drivers consider whether they will be able to properly recharge their vehicle on a more extended trip [50]–[52]. For instance, a study found that an EV with a range of 100 miles would satisfy 50% of one-vehicle households and 80% of multi-vehicle households [53]. Indeed, the notion of battery range and range anxiety is the single most crucial factor in whether a user will consider driving or purchasing an EV [54], [55]. Even though that EVs could cover the majority of current driving ranges, users still desire a higher range, similar to a gasoline vehicle. However, experienced EV drivers are less likely to have higher values of range anxiety than their counterparts [56].

The availability of charging stations is another concern: a study suggests that 71.7% of the respondents were more likely to adopt an EV if charging stations were located at their workplace and trip destinations [57]. Other studies, for instance, note the heightened performance of EVs compared to their counterparts in terms of not only efficiency but acceleration or "smoothness" and "quietness" of the ride [12], [40], [58]. Other studies have also affirmed that EVs require minimal maintenance and generally less effort to own or operate [59], [60].

2.6 Sustainability Values

This final category incorporates sustainability values such as a commitment to low-carbon innovation, or environmental values such as sustainability or futurity. Various studies have demonstrated potential positive spillover-effects in that initial sustainable energy behavior increases the engagement of subsequent sustainable energy behaviors. For example, there is a positive relationship between environmental concern and EV adoption [39], [61]. The expectation of EVs to reduce environmental risks is positively related to EV adoption [61].

Additionally, the environmental performance of EVs is found to be a stronger predictor of attitude and thus purchase intention than price value and driving range [62]. Another study suggests that EV drivers claimed to be engaged in other pro-environmental practices and had changed their attitudes and values after driving an EV [40]. Similarly, the Krupa et al. [57] study reports that those who felt strongly about reducing transportation energy consumption had 71 times greater odds of purchasing an EV, and those who identified strongly about reducing greenhouse gas emissions had 44 times greater odds of purchasing a compact PHEV in comparison with their counterparts. Yet, environmental concern is overshadowed by consumers' unwillingness to pay more than a few thousand U.S. dollars extra for PHEVs[57]. Peters, Werff, and Steg's recent study [63] find that people who adopted an EV for environmental reasons are likely to strengthen their environmental self-identify by using their EV in a more sustainable way, such as emitting as little CO_2 as possible and harming the environment as little as possible when driving. Those consumers with the environment in mind are thus shown to be more likely to engage with EVs, and once bought, engage with other sustainable behaviors.

Furthermore, former research has confirmed that automobile preferences, in particular, relate to a constellation of norms, interpersonal judgments, or affirmation of identity. Some studies analyze the importance of factors such as "interpersonal influence" and social networks as they relate to EV acceptance [64], [65]. Another strand of research finds that EV adoption affirms lifestyle identities related to sustainability or innovativeness, such as being "green" or labelled an "early adopter" [66]–[69], or even notions of security and "cocooning" found in larger vehicles (electric and non-electric), enabling cars to insulate occupants from otherwise noisy or unpleasant aspects of daily life [70]. Lastly come those studies concluding that broader images or symbolism related to confidence in industrial competitiveness, nationalism, security, responsibility, or environmentalism affect electric mobility preferences [66], [71].

2.7 Synthesis and Research Questions

From these six distinct dimensions, we arrive at a synthetic conceptual framework presented in Figure 2, which emphasizes how EV adoption interest will be affected by socio-demographics, technical factors (including V2G capability), economic factors and financial attributes, and behavioral mobility practices and sustainability values. From this synthetic conceptual framework, one can derive specific, testable hypotheses (with research questions) that we introduce in Table 3. Using our framework, we proceed to test these hypotheses using original empirical data from a survey instrument coupled with multiple stages of data analysis below.

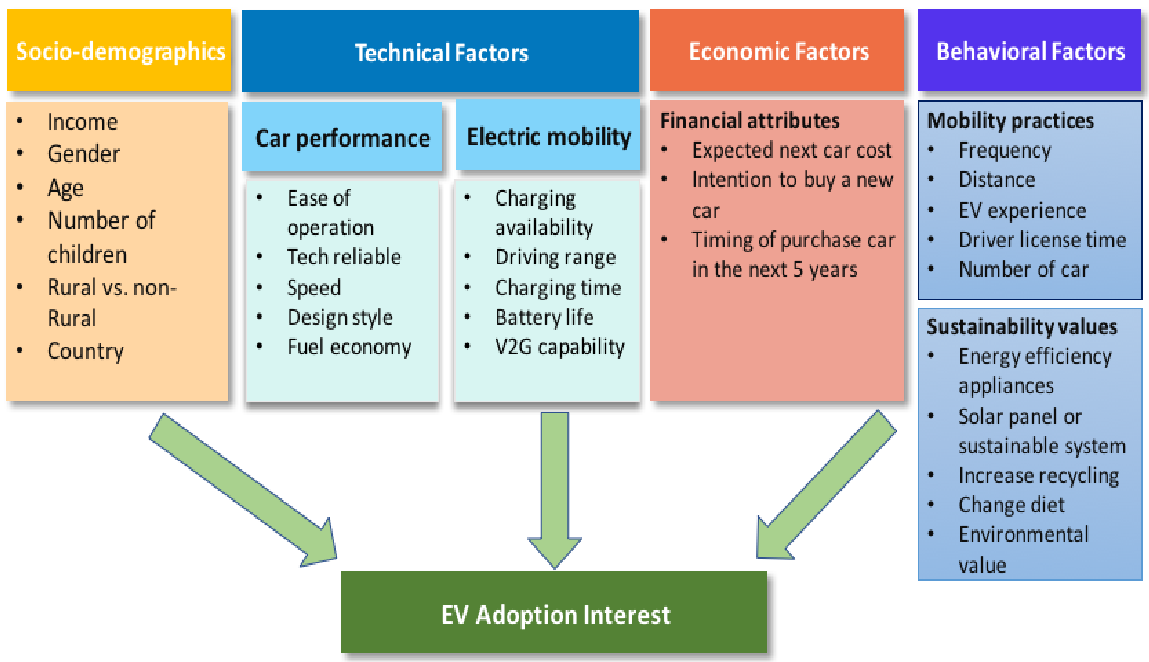

Fig. 2: Multidimensional conceptual framework for EV adoption and the influence of V2G preferences.

Table 3

Dimensions, hypotheses and research eestions

Dimension	Research Question	Hypothesis
Socio-demographics	*RQ1*: What are the essential socio-demographic factors influencing EV adoption with and without considering other factors?	(H1a) younger individuals will have a positive effect on EV adoption after accounting for other factors
		(H1b) men will be more likely to have a higher level of EV adoption after accounting for other factors
		(H1c) higher-income individuals will have a positive effect on EV adoption accounting for other factors

		(H1d) the higher number of children in households have a positive effect on EV adoption after accounting for other factors
		(H1e) residence in a non-rural area has a positive effect on EV adoption accounting for other factors
Financial attributes	*RQ2*: What are the essential financial attributes and mobility patterns influencing EV adoption after accounting for socio-demographics?	(H2a) higher expected car cost will have a positive effect on EV adoption after accounting for other factors
		(H2b) higher intention to buy a new car will affect on EV adoption after accounting for other factors
		(H2c) time of purchasing a car in the next 5 years will have an effect on EV adoption after accounting for other factors
Mobility practices	RQ2*:* What are the essential financial attributes and mobility patterns influencing EV adoption after accounting for socio-demographics?	(H3a) shorter driving distance per day will have a positive effect on EV adoption after accounting for other factors
		(H3b) the higher number of cars in the household will have a positive effect on EV adoption after accounting for other factors
		(H3c) driving experience with an EV will have a positive effect on EV adoption after accounting for other factors
		(H3d) driving regularly will affect EV adoption after accounting for other factors
		(H3e) the longer period of time of owning a driver license will have affect EV adoption after accounting for other factors
Electric mobility attributes	RQ3: What are the distinct electric mobility attributes influencing EV adoption after accounting for other factors? RQ4: What are the different electric mobility preferences across current and former EV owners, and conventional vehicle owners?	(H4a) public charging station availability will have a positive effect on EV adoption after accounting for other factors
		(H4b) the range will have a positive effect on EV adoption after accounting for other factors
		(H4c) shorter charging time will have a positive effect on EV adoption after accounting for other factors
		(H4d) battery life will have a positive effect on EV adoption after accounting for other factors
		(H4e) V2G capability will have a positive effect on EV adoption after accounting for other factors
Conventional vehicle attributes	RQ5: What are the distinct conventional vehicle attributes influencing EV adoption after accounting for other factors? RQ6: Is there a carry-over effect from conventional vehicles to electric mobility attributes in influencing EV adoption?	(H5a) ease of operation will have a positive effect on EV adoption after accounting for other factors
		(H5b) technical reliability will have a positive effect on EV adoption after accounting for other factors
		(H5c) speed & acceleration will have a positive effect on EV adoption after accounting for other factors
		(H5d) design & style will have a positive effect on EV adoption after accounting for other factors
		(H5e) fuel economy and financial savings will have a positive effect on EV adoption after accounting for other factors
Sustainability values (and activity)	RQ7: What values influence EV adoption, and do these spill over into other areas of	(H6a) energy efficiency appliance installation will have a positive effect on EV adoption after accounting for other factors

	sustainable behavior after accounting for other factors?	(H6b) solar panel or other sustainable system adoption will have a positive effect on EV adoption after accounting for other factors
		(H6c) increase recycling will have a positive effect on EV adoption after accounting for other factors
		(H6d) changing diets by eating less meat or local products will have a positive effect on EV adoption after accounting for other factors
		(H6e) high environmental values will have a positive effect on EV adoption after accounting for other factors

Source: Authors. Note: we predicted one individual hypothesis by controlling all other variables in Model 5 of the analysis.

3. Method

To empirically test and validate our framework, hypotheses, and questions, we relied on original data collected from a large-scale survey distributed throughout the Nordic region. This section summarizes our sampling strategy, survey procedure, and data analysis techniques.

3.1 Participants and Sampling

An internet-based questionnaire was designed with Qualtrics survey software and administered through Qualtrics Paid Panel Service, a popular used online data collection platform by researchers. Eligible participants were selected from the current residence in Denmark, Finland, Iceland, Norway, or Sweden, at least 18 years old. Among the 4885 participants, 48.29% were females, and 50.26% were males, and 1.45% responded with 'prefer not to say' or 'other'. Average age was 42.12 (standard deviation, *SD* = 15.78). Approximately 62% had no children, 14.7% had one child, 12.2% had two children, and 5.6% had three or more children. The most chosen household income bracket was €30,001- €50,000 (about 22.44%), followed by $€10,001- €30,000 (about 21.72%). 40.53% of respondents had a post-graduate degree, 25.3% an undergraduate degree, 16.87% a secondary education, and 17.3% did not report or reported 'other.' Denmark had the largest number of respondents at 22.25%, followed by Finland (22.03%), Norway (20.96%), Sweden (20.82%), and Iceland (13.94%). Approximately 45.32% of respondents lived in a suburban area, followed by 35.64% in an urban area, and 18.98% in a rural area.

3.2 Survey Instrument

The structured questionnaire consisted of four parts with 44 total questions (including an online choice experiment, which was not analyzed here). The first part asked about vehicle ownership for both conventional fuel vehicle and EVs; intention to purchase an EV (our dependent varaible, DV; referring to as EV adoption from here on); mobility practices, namely the frequency of driving (i.e., regular driver or not), daily driven distance (kilometer per day); the time having a drivers' license, number of cars; and financial attributes including expected costs of the next vehicle and new vehicle purchase intention as well as time frame of purchase a car in next five years. The second part asked about the vehicle attributes that the respondents valued most (or least) when considering purchases in the forms of mobility, such as speed and acceleration, design and style, fuel economy and financial savings, and technological reliability. This part also asked five questions specifically about the importance of EV attributes, including charging availability, driving range, battery life, charging time, and V2G capability. The third part of the survey asked respondents about their sustainability preferences and activities (e.g., energy efficiency appliance installation, solar panel, or sustainable energy system investment, environmental values). The final part of the survey includes demographics such as age, gender, income, number of children, living location (i.e., rural or non-rural), country, and so on. All measures except for socio-demographics, EV driving experience, and sustainability activities were estimated by participants' responses to the items with a 5-point Likert-type scale.

3.3 Data Analysis Strategy

To analyze our data, we start from descriptive statistics and analyze relationships among predictors using Pearson correlation, Chi-square testing, and finally fit hierarchical multiple regression models and Analysis of Variance (ANOVA) to answer the research questions and test our hypotheses. All analyses were performed using IBM SPSS 24.0. The basic descriptive statistics were first used to analyze sample characteristics. Finally, a hierarchical five-stage analysis of multiple regression models was performed step by step to analyze how well our independent variables (IVs),including socio-demographics, mobility practices, financial attributes, vehicle performance, electric mobility, and sustainability value, predicted EV adoption intention. We adopted the hierarchical regression analysis because it allows this study to analyze successive linear regression models by entering IVs sequentially into models, in line with the current theory and logic of research [72], [73]. That is, hierarchical regression allows this research to test for the incremental influence of our proposed six dimensions of socio-demographics, mobility practices, financial attributes, conventional fuel car performance, electric mobility, and sustainability value, step by step, by accounting for other factors' influence as opposed to a single multiple regression which would not see the changes from model to model.

Specifically, there are two advantages of hierarchical regression, and these include: (a) the extraction of as much causal inference as the data will allow and (b) the estimation of the total variance of the criterion attributed to an IV which depends on its relationship with the criterion and other variables that have been entered into the model, as measured by the change in R^2 [72], [73]. For each additional IV, the model calculates R^2 and partial coefficients of each variable. Consequently, the change in R^2 (ΔR^2) and its corresponding change in F (ΔF) and p values are the greatest interest in our statistical analysis [73], [74]. The linearity assumption and outlier examination were examined as explained further below. A p-value of below 0.05 was used to indicate statistical significance, as is the practice in the majority of social science studies [75]. Bootstrapping tests with 5000 resamples and a 95% bias-corrected confidence interval were used to test the robustness of the regression coefficients. However, this paper reports the results from the regular regression models without the bootstrapping tests since both results were similar.

3.4 Regression Diagnostics

Before testing the hypotheses, several steps of regression diagnostics were conducted to evaluate the model assumptions and influential cases. We first checked regression assumptions, including linearity, homoscedasticity, multicollinearity, and normality. An examination of correlations revealed that no IVs were highly correlated. Regarding the collinearity statistics, the variance inflation factor (VIF) scores were all within accepted limits (1.06 to 2.06) indicating multicollinearity among all the variables was not a problem [76] and not causing high standard errors among the predictors. VIF scores show how much the variance of an estimated regression coefficient increases if the explanatory variables are correlated. In this paper, a VIF value of 3.3 was used [77]. After model selection, diagnostics were run to check the validity of the model in meeting the assumptions for linear regression. A Shapiro-Wilks test was conducted to check for non-normality. The null-hypothesis for normality was rejected; however, this test is known to be overly sensitive with large sample sizes.

A visual inspection of the diagnostic plots was further conducted to assess normality. All the models of the residuals were inspected. For the final model, the histogram of standardized residuals was approximately normal if slightly left-skewed (skew = -0.73, standard error = 0.04) and leptokurtic (kurtosis = 0.25, standard error = 0.09). Additionally, we conducted a visual inspection of the diagnostic plots. Inspection of the *P-P* and *Q-Q* plots of residuals revealed that the residuals were nearly normal, and showed no extreme deviations from the expected; however, the right tail of the *Q-Q* plot has a slight deviation from the expected normal. The residual versus fitted values plot revealed a few outliers but has no obvious patterns and had fairly even variation and spread. Furthermore, it showed that they were linear over a wide range of values. The residuals versus fitted values indicate that the residuals are nearly uncorrelated to the fitted values. Finally, normal curve plots for all the variables did not indicate large deviations from normality.

4. Results

This section presents our main findings, organized around descriptive statistics before moving to the step-by-step hierarchical multiple regression analyses.

4.1 Descriptive Statistics

We first present the summary of descriptive stasttics on the major variables analyzed in study. Approximately 70.40% of the participants drove regularly, while 29.60% did not drive regularly. 62.01% of participants have had their driver's license for longer than ten years. Only 22.05% of participants had experience with driving an EV. Regarding drive distance, 30.03% drove 20 kilometers or less a day. When asking about car ownership, 48.82% of participants owned one car, and 23.8% of participants owned two cars, while 20.02% did not own a car. About 56.64% were looking to purchase a new car in the next five years. Of those looking to buy a new vehicle, 26.9% of the participants expect to spend between €10,000 and €20,000 on their next car, while 35.82% were looking to spend more than €20,000. Table 4 shows the percentages behind sustainability values & conventional and electric vehicle performance. In terms of conventional vehicle attributes, fuel economy and saving money was the most important attribute to 88.11% of participants, followed by technology reliability (84.75%), ease of operation (80.15%), and speed and acceleration (56.36%). Among EV specific preferences, battery life was the most important attribute (91.93%), followed by public charger availability (88.78%), charging time (87.8%) and driving range (86.61%); yet, only 55.03% of participants thought V2G capability was important.

In terms of correlations, all IVs were moderately correlated with EV adoption interest (DV). Among all the variables, new vehicle purchase intention and car purchase in the next five years were correlated as well ($r = 0.66$, $p < 0.001$), followed by EV charging time and EV public charger availability ($r = 0.58$, $p < 0.001$), EV battery life and EV public charge availability ($r = 0.58$, $p < 0.001$), and EV driving range and EV battery life ($r = 0.56$, $p < 0.001$). As mentioned earlier, none of the IVs were highly correlated based on the VIF scores, and are, therefore, suitable for being IVs of multiple linear regression analysis.

Table 4
Percentage of sustainability activities and conventional and EV attribute preferences

Variable	Category

	Yes	No			
Energy efficiency appliances	39.90%	58.94%			
Solar panel investment	10.19%	88.56%			
Increased recycling	65.90%	33.04%			
Changed diet	48.66%	50.22%			
Variable	Category				
	Very Important	Somewhat important	Neither important or unimportant	Somewhat unimportant	Very unimportant
EV attribute preference:					
EV public charging	64.01%	24.77%	8.19%	1.39%	1.54%
EV driving range	54.51%	32.10%	10.58%	1.25%	1.49%
EV charging time	51.50%	36.27%	9.27%	1.49%	1.39%
EV battery life	72.16%	19.77%	5.94%	0.76%	1.33%
V2G capability	21.56%	33.47%	33.61%	6.33%	4.97%
Conventional car attribute preference:					
Ease of operation	38.14%	42.01%	15.91%	2.31%	1.45%
Tech reliability	51.81%	32.94%	11.89%	2.05%	1.17%
Speed & acceleration	12.14%	44.22%	29.64%	8.97%	4.99%
Design & style	18.10%	46.43%	22.50%	8.82%	4.12%
Fuel economy	52.24%	35.87%	8.64%	1.68%	1.57%
Personal value:					
Environmental values	20.45%	47.25%	26.88%	3.34%	2.09%

4.2 Hierarchical Regression Analysis

This section describes the hierarchical multiple regression analysis performed to test the regression models and the hypothesized relationships. Model 1 was first analyzed by socio-demographic variables only since researchers suggest that static variables of interest (e.g., gender, age, income) should be entered into the models before dynamic variables in subsequent steps [72]. Additionally, socio-demographic factors are generally considered as control variables in many EV and other technology acceptance studies [62], [78], [79]. Model 2 was analyzed by adding mobility practices (e.g., driving regularly, number of cars, daily driving distance, and number of years of having a driver's license) and financial attributes to Model 1. Mobility practices and financial attributes (e.g., expected costs, intention to buy a new vehicle, and timeframe of purchase) are more static than other attitudinal variables such as vehicle attribute preferences and direct measures of intention to buy an EV in terms of driving behavior and economic factors; therefore, they were entered in the second step before electric mobility.

Model 3 was analyzed by adding electric mobility into Model 2 because we first wanted to examine participants' preference for electric mobility attributes without knowing the effect of more general car attributes. Model 4 was analyzed by adding conventional vehicle attributes to Model 3 because we wanted to examine if vehicle performance attributes have added carry-over effects to the electric mobility attributes on EV adoption based on our research questions. Finally, Model 5 was analyzed by adding four sustainability behaviors, including installed energy efficiency appliances, invest in solar panels or sustainable energy systems, recycling behavior, eating less meat or local products, and environmental value to Model 4. The reasoning of this step is to examine if there is a spillover effect of sustainability values through both conventional vehicle and electric mobility attributes on EV adoption interest. They were entered in the last step due to the indirect measure of interest in purchasing a vehicle. Table 5 presents standardized regression coefficients to allow a comparison of the impact of IVs and adjusted coefficients of determination. The *F*-statistic is statistically significant ($p < 0.001$) in all five models. When interpreting the results of the hierarchical regression, it is recommended to use an adjusted coefficient of determination, as it accounts for sample size and the number of IVs.

4.3 Effect of socio-demographics (Model 1)

To answer the first part of *RQ1*, our results of Model (1) revealed that socio-demographics explained 4.5% of the variability in EV adoption with $R^2 = 0.045$, adjusted $R^2 = 0.043$, $F(9, 3306) = 17.38$, $p < 0.001$. The standardized coefficient *Beta* refers to the number of standard deviation changes that are to be expected in the DV for a one standard deviation change in the predictor variable (or IV). As shown in Table 5, among all the socio-demographics, younger ($\beta = 0.08$; $p < 0.001$), males ($\beta = .05$; $p < 0.001$), those with higher income ($\beta = 0.10$; $p <$

0.001), and higher number of children (β = 0.05; p < 0.001) and Iceland residents (β = 0.15; p < 0.001) were more interested in purchasing an EV. A rural location was not a significant factor.

Table 5

Results of hierarchical linear regression models on EVadoption

Variables	Model 1	Model 2	Model 3	Model 4	Model 5
Step 1 Socio-demographics:					
Age	-0.08***	-0.05*	-0.07**	-0.09***	-0.09***
Gender	0.04**	0.03	0.04*	0.07***	0.10***
Income	0.10***	0.10***	0.10***	0.09***	0.08***
Finland	0.00	0.04	0.04	0.03	0.01
Sweden	0.04	0.06**	0.06**	0.05*	0.03
Iceland	0.15***	0.19***	0.18***	0.15***	0.12***
Denmark	0.00	0.02	0.02	0.01	-0.01
Number of children	0.04**	0.05**	0.05**	0.05**	0.04*
Rural vs. non-rural	0.03	-0.01	-0.01	0.00	0.01
***Step 2 Mobility practices and financial attributes**:*					
Driving KM per day		-0.10***	-0.11***	-0.10***	-0.09***
Regular driver or not		0.03	0.03	0.04	0.04
Number of cars		-0.14***	-0.14***	-0.11***	-0.10***
Has driven an EV		0.13***	0.13***	0.11***	0.09***
Drivers’ license time		-0.01	0.00	0.00	0.01
Expected car cost		0.04*	0.04*	0.06**	0.05**
Buying new car		0.06**	0.06*	0.05*	0.04
Within 5 years		0.00	0.00	0.00	0.00
Step 3 Electric mobility:					
Charging availability			0.04*	0.01	0.00
Charging time			-0.02	-0.05*	-0.04*
V2G capability			0.11***	0.09***	0.04**
Battery life			0.03	-0.01	0.00
Driving range			0.02	-0.02	-0.03
Step 4 Conventional car attributes:					
Fuel economy				0.22***	0.18***
Ease of operation				0.08***	0.05**
Tech reliability				0.10***	0.07***
Speed & acceleration				-0.02	-0.02
Design & style				-0.03	-0.01
Step 5 Sustainability activities & value:					
Increased recycling					0.08***
Solar panels					0.04*
Changed diet					0.07***
Efficient appliances					0.04*
Environmental value					0.17***
R^2	0.05	0.09	0.11	0.18	0.24
ΔR^2	0.04	0.09	0.10	0.17	0.23
ΔF	17.38***	20.45***	14.19***	56.70****	51.35***

Note: * p < 0.050. ** p <0. 01 *** p < 0.001. Gender (male =1), rural vs. non-rural (rural =1), diving regularly (regular driver =1) and county (Norway is a reference group) were dummy coded.

We further examined the differences in EV adoption interest among the five countries by performing a Chi-square test of independence to compare three different EV interest groups including interested (including very and somewhat interested), neutral (neither interested or not interested) and not interested (including very and somewhat uninterested). A significant difference in EV adoption interest was found, $\chi^2(4) = 83.83$, $p = 0.001$). Among the interested groups, all the countries had a high-interest rate in EV adoption (70.3%-89.5%), with Iceland having the highest interest rate at 89.5%. Among the uninterested groups, the percentage ranged from 10.5%-29.7% across the five countries, with Iceland having the lowest rate, 10.5%.

4.4 Effects of mobility practices and financial attributes (Model 2)

To answer *RQ2*, Model 2 revealed that the entry of the mobility practices and financial attributes to Model 1 leads to an overall significant model (F (17, 3298) = 19.26, $p < 0.001$) that explains 8.9% of the variation, with an adjusted R^2 of 9.0% (see Table 4). In comparison with Model 1, there was a statistically significant improvement in adjusted R^2change (as the percentage of variability accounted for went up from 4.3% to 9.0%), F (8, 3298) = 20.45, $p < 0.001$. Among all the demographics, age, income, the number of children, Iceland (the strongest predictor in Model 2) and Sweden were significant predictors, in contrast, gender became insignificant, and living in rural areas remained insignificant. As for mobility practices, a higher number of cars in the household ($\beta = -0.14$; $p < 0.001$) had a negative effect on EV adoption interest. Former EV driving experience ($\beta = 0.13$; $p < 0.001$) was a positive predictor. Driving regularly and having a longer period of a driver's license were not related to EV adoption; however, those who drove a longer distance per day ($\beta = -0.10$; $p < 0.001$) were less interested in adopting an EV. As for financial attributes, a higher expected cost for the next car ($\beta = 0.04$; $p < 0.5$) and intention to buy a new car ($\beta = 0.06$; $p < 0.01$) had positive effects on EV adoption whereas looking for a car in the next five years was not a significant predictor.

4.5 Effect of electric mobility (Model 3)

To answer *RQ*3, the results of Model 3 revealed that socio-demographics, and mobility practices, financial attributes and electric mobility explained 10.9% of the variation, with an adjusted R^2 of 10.4%, $F(22, 3293) = 18.40$, $p < 0.001$. Thus, adding Model 2 to Model 3 (see Table 4), offered only a slight improvement in adjusted R^2change of 1.9%, F (5, 3293) = 14.19, $p < 0.001$. The change in R^2 is an indicator to evaluate how much predictive power is added to a regression model by the addition of other variables in the next step, which implying that adding electric mobility related variables did not add as much explanatory power as one might have expected. In comparison with Model 2, age, income, the number of children and residents in Sweden and Iceland remained significant among the socio-demographic factors, whereas gender became significant in Model 3. Driving distance, number of cars, EV driving experience, higher expected car costs, and intention to buy a new car also remained significant. Males ($\beta = 0.04$; $p < 0.05$) were more interested in adopting an EV than females after considering EV attributes, socio-demographics, mobility practices, and financial attributes. Among all the EV attributes, V2G capability ($\beta = 0.11$; $p < 0.001$) was the strongest positive predictor, and public charging availability ($\beta = 0.04$; $p < 0.05$) was also positively related to EV adoption. However, battery life, charging time, and driving range were not statistically significant.

4.6 Effects of conventional vehicle performance attributes (Model 4)

To answer both *RQ5* and *RQ6*, the Model 4 indicated that socio-demographics, mobility practices, financial attributes and vehicle performance and electric mobility explained 18% of the variation, with an adjusted R^2 of 17.3%, $F(27, 3288) = 26.76$, $p < 0.001$; with a good improvement in adjusted R^2change of 6.9%, F (5, 3288) = 56.79, $p < 0.001$ by adding Model 3 to Model 4. This result suggests that adding conventional car attributes improved the model significantly as compared to the model to the model with only electric mobility after accounting for socio-demographics, mobility practices, and financial attributes. Compared with Model 3, age, gender, income, Sweden, and Iceland, the number of children remain significant among the socio-demographics. Driving distance, number of cars, EV driving experience, higher expected car costs, and intention to buy a new car also remained significant. However, the effects of electric mobility changed after entering conventional vehicle attributes. Specifically, V2G capability remained a significant predictor, but EV charging time became significant, whereas public charging availability lost its predictive power. Among conventional vehicle attributes, fuel economy and financial savings ($\beta = 0.22$; $p < 0.001$), ease of operation ($\beta = 0.08$; $p < 0.001$) and technical reliability ($\beta = 0.10$; $p < 0.001$) were significant predictors. Overall, fuel economy and financial savings were the strongest predictors in Model 4.

4.7 Effects of sustainability values (Model 5)

To answer both parts of *RQ*1 and *RQ*7, four sustainable behaviors and environmental values were added to Model 4 in Model 5. The influence of these constructs was confirmed in numerous former studies, which is the main reason for adding these variables in the last model (Model 5) to test our research question about the spillover effects. Overall, the predictive power of the model was significantly higher than in Model 4, and all together explained 24% of the variation, with an adjusted R^2 of 23.2%, $F(32, 3283) = 37.33$, $p < 0.001$. This model has improved 5.9% in adjusted R^2 change from Model 4, F (5, 3283) = 51.35, $p < 0.001$. The significant predictors in socio-demographics, mobility practices, and financial attributes remained unchanged. Regarding electric mobility, V2G capability remained a significant positive predictor, and EV charging time was also a positive predictor, In contrast, public charging availability, battery life, and range were not related to EV adoption. Three conventional vehicle attributes, including fuel economy and financial savings, ease of operation, and technical reliability, remained the same. All the predictors for the sustainability value including solar or other sustainable energy system investments ($\beta = 0.04$; $p < 0.05$), changed diets ($\beta = 0.04$; $p < 0.05$), recycling ($\beta = 0.08$; $p < 0.001$), energy efficiency appliance installation ($\beta = 0.04$; $p < 0.05$), and environmental value ($\beta = 0.17$; $p < 0.001$) had positive effects on EV adoption. Taken together, the conventional vehicle attribute on fuel economy and financial savings, and overall environmental value were the two strongest predictors of EV adoption after accounting for all other variables.

4.8 Results of ANOVA on electric mobility across groups

To answer *RQ*4, a one-way between-subject ANOVA was conducted to compare the difference of five EV attributes among three groups, including current EV, former EV, and conventional fuel car owners (see Figure 3). For driving range, there was a significant difference among the three group, at the $p < 0.05$ level, $F(2, 3687) = 7.13$, $p = 0.001$. We further report the post hoc test to compare the mean differences in the driving range to every group comparison. Post-hoc comparisons using the Tukey HSD test indicated that the mean score of the driving range attribute was significantly lower in former EV owners ($M = 4.20$, $SD = 0.74$) than conventional fuel car owners ($M = 4.47$, $SD = 0.76$) and EV owners ($M = 4.46$, $SD = 0.69$). For battery life, there was a significant difference among the three groups, at the $p < 0.05$ level, $F(2, 3688) = 40.17$, $p = 0.000$. The mean score of battery life attribute in conventional car owners was significantly higher ($M = 4.70$, $SD = 0.65$) than in EV owners ($M = 4.43$, $SD = 0.82$) and former EV owners ($M = 4.23$, $SD = 0.94$). EV owners also had a significantly higher mean score of battery life than that of former EV owners. For changing time, there was also a significant difference among the three groups, at the $p < 0.05$ level, $F(2, 3688) = 18.60$, $p = 0.000$. The mean score of charging time attribute in conventional car owners was significantly higher ($M = 4.42$, $SD = 0.76$) than EV owners ($M = 4.20$, $SD = 0.86$) and former EV owners ($M = 4.08$, $SD = 0.85$). However, there was not a significant difference between the current and former EV owners. Regarding public charging availability, there was a significant difference among three groups, at the $p < 0.05$ level, $F(2, 3685) = 47.09$, $p = 0.000$. The mean score among conventional car owners was significantly higher ($M = 4.56$, $SD = 0.74$) than EV owners ($M = 4.15$, $SD = 0.98$) and former

EV owners (M = 4.11, SD = 0.96). However, there was not a significant difference between the current and former EV owners. Finally, results of ANOVA suggest that there was a significant difference among in V2G capability preferences, $F(2, 3686) = 8.03$, $p = 0.000$; the mean score in former EV owners was significantly higher (M = 3.80, SD = 1.04) than EV owners (M = 3.38, SD = 1.30) and conventional fuel car owners (M = 3.63, SD = 1.02).

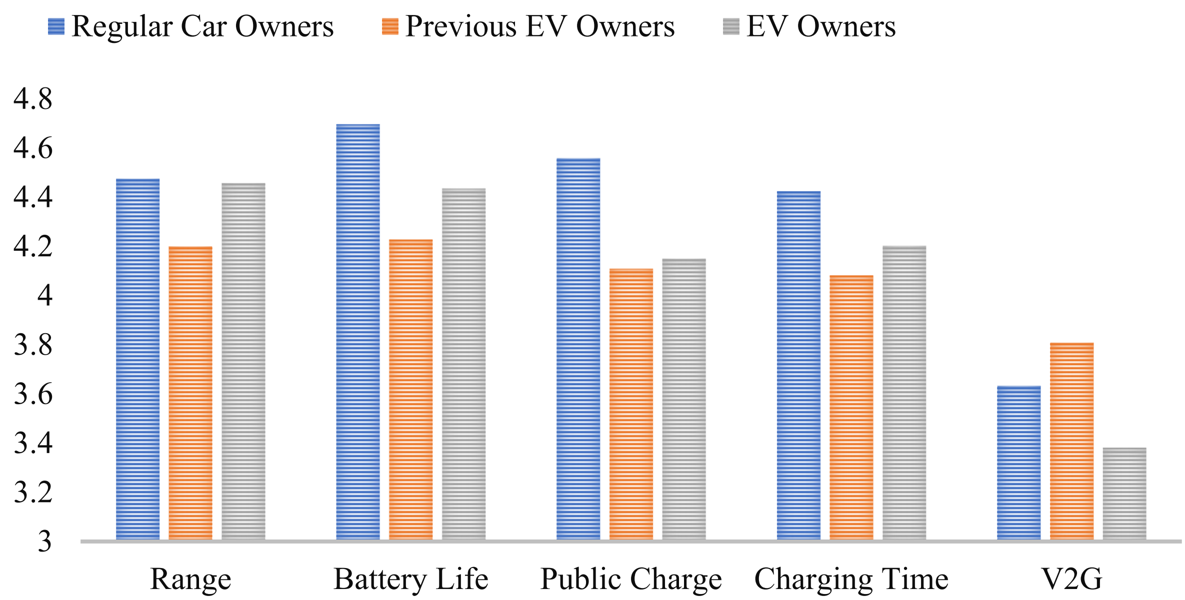

Fig. 3: Mean difference in EV attributes across conventional vehicle owners, formal EV and current EV owners based on the 1-5 Likert-scale

5. Discussion and Findings

This study investigated the interconnected effects of socio-demographic, technical, economic, and behavioral factors on stated preference for EVs and V2G. Table 6 offers a summary of our results based on hypotheses and research questions. Overall, we find that the effect of certain socio-demographics on EV adoption interest remains rather consistent across the five tested models.

Table 6
Summary of results for hypotheses and tesearch questions

Dimension	Research Question	Hypothesis	Models	Result

Socio-demographics	*RQ1*: What are the essential socio-demographic factors influencing EV adoption with and without considering other factors?	(H1a) younger individuals will have a positive effect on EV adoption after accounting for other factors	1, 5	Supported
		(H1b) men will be more likely to have a higher level of EV adoption after accounting for other factors		Supported
		(H1c) higher-income individuals will have a positive effect on EV adoption accounting for other factors		Supported
		(H1d) the higher number of children in households have a positive effect on EV adoption after accounting for other factors		Supported
		(H1e) residence in a non-rural area has a positive effect on EV adoption accounting for other factors		Rejected
Financial attributes	*RQ2*: What are the essential financial attributes and mobility patterns influencing EV adoption after accounting for socio-demographics?	(H2a) higher expected car cost will have a positive effect on EV adoption after accounting for other factors	2, 5	Supported
		(H2b) higher intention to buy a new car will affect on EV adoption after accounting for other factors		Supported
		(H2c) time of purchasing a car in the next 5 years will have an effect on EV adoption after accounting for other factors		Rejected
Mobility practices	RQ2*:* What are the essential financial attributes and mobility patterns influencing EV adoption after accounting for socio-demographics?	(H3a) shorter driving distance per day will have a positive effect on EV adoption after accounting for other factors	2, 5	Supported
		(H3b) the higher number of cars in the household will have a positive effect on EV adoption after accounting for other factors		Rejected
		(H3c) driving experience with an EV will have a positive effect on EV adoption after accounting for other factors		Supported
		(H3d) driving regularly will affect EV adoption after accounting for other factors		Rejected
		(H3e) the longer period of time of owning a driver license will have affect EV adoption after accounting for other factors		Rejected
Electric mobility attributes	RQ3: What are the distinct electric mobility attributes influencing EV adoption after accounting for other factors? RQ4: What are the different electric mobility preferences across current and former EV owners, and	(H4a) public charging station availability will have a positive effect on EV adoption after accounting for other factors	3, 5	Rejected
		(H4b) the range will have a positive effect on EV adoption after accounting for other factors		Rejected
		(H4c) shorter charging time will have a positive effect on EV adoption after accounting for other factors		Supported
		(H4d) battery life will have a positive effect on EV adoption after accounting for other factors		Rejected
		(H4e) V2G capability will have a positive effect on EV adoption after accounting for other factors		Supported

	conventional vehicle owners?			
Conventional vehicle attributes	RQ5: What are the distinct conventional vehicle attributes influencing EV adoption after accounting for other factors? RQ6: Is there a carry-over effect from conventional vehicles to electric mobility attributes in influencing EV adoption?	(H5a) ease of operation will have a positive effect on EV adoption after accounting for other factors	4, 5	Supported
		(H5b) technical reliability will have a positive effect on EV adoption after accounting for other factors		Supported
		(H5c) speed & acceleration will have a positive effect on EV adoption after accounting for other factors		Rejected
		(H5d) design & style will have a positive effect on EV adoption after accounting for other factors		Rejected
		(H5e) fuel economy and financial savings will have a positive effect on EV adoption after accounting for other factors		Supported
Sustainability Values	RQ7: What values influence EV adoption, and do these spill over into other areas of sustainable behavior after accounting for other factors?	(H6a) energy efficiency appliance installation will have a positive effect on EV adoption after accounting for other factors	5	Supported
		(H6b) solar panel or other sustainable system adoption will have a positive effect on EV adoption after accounting for other factors		Supported
		(H6c) increase recycling will have a positive effect on EV adoption after accounting for other factors		Supported
		(H6d) changing diets by eating less meat or local products will have a positive effect on EV adoption after accounting for other factors		Supported
		(H6e) high environmental values will have a positive effect on EV adoption after accounting for other factors		Supported

Source: Authors

As Table 5 indicates, males were consistently more interested in EVs than females, affirming existing literature on early EV adoption and its mainstream market [12]–[14], [17]. Notably, we find that younger individuals are likely to show more interest in EVs. This result contrasts with some of the existing EV adoption literature that is focused on EV adoption [13], [14], [16], [17], suggesting that while younger individuals are more interested in EVs, it is older consumers who have had purchasing power. Therefore, one could expect EV adoption rates to increase once the market offers a broader range of EV models at more affordable prices. In terms of living area, we did not find significant results in EV adoption interest between rural and urban spaces, refuting some conceptualizations of the EV as an "urban car."

When considering the effects of mobility practices and financial attributes after controlling for socio-demographics, three essential findings emerge. First, people who had more vehicles were (perhaps unexpectedly) less interested in adopting an EV. Second, in line with the literature, people who had driven an EV before expressed more interest in choosing one. Third, those with longer commutes were less interested in adopting an EV. In particular, the first point contrasts with the idea of EVs as a second car [35], [80], as we find that individuals who expressed more interest on EVs can envision it as their primary or only car in the household. More importantly, this remarks on the evolving social perception around EVs: as the primary form of driving or an simple substitution for a petrol or diesel vehicle.

When looking more deeply into electric mobility (Model 3) and conventional vehicle attributes (Model 4), other salient points emerge. Both EV charging time and V2G attribute remained significant after adding conventional vehicle attributes (and remained so after adding sustainability values in Model 5). In particular, combining V2G capability to EVs can foster EV adoption, considering V2G can add a revenue stream for V2G-EV owners [17]. Hence, both industry and policymakers could look at promoting V2G as part of their EV deployment strategies, considering that beyond the potential benefits V2G systems, the technology can contribute to reaching EV deployment targets. However, the regression weight of V2G attributes slightly decreases after adding conventional vehicle attributes and sustainability values (Model 5), while we found a negative relationship between charging time and EV adoption interest. EV battery life, EV driving range, and EV public charging availability and two conventional vehicle attributes, including speed and acceleration and design and style, do not seem to matter much across any of the models after considering all other factors.

Furthermore, people still use conventional vehicle attributes as an essnetial reference point while considering whether to adopt an EV. This fact was evidenced by adding five conventional vehicle attributes (Model 4) to the electric mobility model (Model 3). Here, Model 3's variance increased, indicating conventional vehicle attributes did contribute significantly to electric mobility attributes, thus adding more explanatory power and suggesting a carry-over effect from conventional vehicle attributes to EV adoption interest.

When examining the overall profile of Model 4 (and even Model 5), we find that people who value fuel economy, ease of operation, and technological reliability are more interested in adopting an EV. While this finding is in line with the literature as it highlights some of the EV benefits in comparison to conventional cars (like operational savings from a higher drive efficiency and reduced maintenance costs), it also reiterates that EVs are mostly advertised on their efficiency and environmental attributes (with the exception of Tesla) and therefore are appealing to cost and environmentally sensitive consumers. As research has shown; however, current EV adoption is led by a sense of status. Hence, our results indicate that EV promotion strategies should also emphasize the technological aspects of EVs, such as better acceleration or ease of operation.

Moreover, adding sustainability value (Model 5) improved the explanatory power of socio-demographics, mobility practices, financial attributes, electric mobility, and conventional vehicle attributes on EV adoption interest. Installing energy-efficient appliances, investing in solar PV panels or other renewable energy systems, recycling and eating less meat or more local products, as well as identifying with pro-sustainable values are positive predictors. However, the regression weights of fuel economy and financial savings, ease of operation and technology reliability decreased slightly, highlighting the influence of sustainability factors and their spill-over effects on EV adoption: engaging in one sustainable energy behavior influences the likelihood of engaging in subsequent similar behaviors [63]. Taken together, both fuel economy and financial savings, coupled with environmental values, were the strongest predictors.

Notably, as we compared three distinct groups—conventional fuel vehicle owners, former EV owners, and EV owners— we found that EV experience does influence the perception and importance around EV attributes. The driving range was ranked less critical to former EV owners than a conventional car and current EV owners, indicating that it may not be the reason for those owners to give up EVs [51]. Battery life was ranked more critical to conventional fuel vehicle owners than current and former EV owners, which is logical and potentially points to that post-purchase EV experience may disperse the questions around battery lifetime. Regarding public charging availability, conventional vehicle owners ranked this attribute significantly more important than EV owners and former EV owners; however, there was not a significant difference between current and former EV owners, indicating that those with EV experience only rarely use public charging stations. Finally, former EV owners considered V2G to be more important than current EV and conventional car owners, implying that V2G could be the marginal incentive that would be the "tipping point."

6. Conclusion

Ultimately, these collective insights from the analysis of six interconnected dimensions translate into some compelling implications. Socio-demographic attributes of potential adopters, such as age, gender, or income, are essential. Still they are no less or more important than other characteristics, such as financial considerations, experience with an EV, or having values orientated towards sustainability. EV adoption is shaped simultaneously by extrinsic factors (e.g., availability of charging infrastructure, and vehicle attributes) as well as intrinsic factors (e.g., demographics but also environmental values and personal preferences and finances (e.g. expected purchase prices of next car) [81].

More importantly, although EVs might not be not a top choice for many of our survey respondents, they may still be considered in their decision-making process. Our study, for example, indicates an attribute carryover effect from specific conventional vehicle attributes (e.g., fuel economy and financial savings) to EV adoption. That carryover might occur when consumers make decisions that are consistent with the beliefs that align with their former first preference [82]. This process happens because consumer memories about utility gained from differentiating attributes in past conventional vehicle choices influence their inferred preferences in any subsequent decision about EVs. Note that these carryover attributes from conventional vehicle attributes, including fuel economy and financial savings, ease of operation, and technology reliability, are particularly relevant to EV attributes.

Additionally, our results have new policy implications. While much of EV policy literature focuses on price or charging infrastructure [32], the results here show that the V2G capability attribute was the most critical factor of electric mobility in determining prospective EV adoption. While V2G is often framed as a technology that will develop much further down the road [83], it fact may make more sense for policymakers to focus *less* on current policy schemes and instead focus on implementing V2G capability first. Indeed, V2G could be the tipping point that drives EV adoption, not vice versa, as the literature often assumes. In addition to driving EV adoption, V2G may also be a more cost-effective policy solution in two ways. First, as theV2G has its own environmental and economic benefits compared to public charger investments, which has no additional societal benefit beyond increased EV adoption. Second, considering V2G as part of an integrated smart power system that may also provide a cost-effective method, as opposed to further expensive grid developments, in integration renewable energy to the grid and decarbonizing the power sector.

Lastly, our study shows that potential EV adopters are also more likely to pursue other low-carbon practices such as purchasing PV panels, reducing waste, or implementing energy-efficiency upgrades, and vice versa. This spell-over effect reminds us that EV adoption is inherently multidimensional, holistic, and relational. EV and V2G adoption preferences weave together multidimensional attributes spanning demographics, vehicle attributes, commensurability with EV infrastructure, cost considerations, former mobility practices, and values. They create together intrinsic and extrinsic factors, and are embedded in a web of non-transport related practices (and lifestyles) connected to energy, buildings, and diet, to name a few. Systematically understanding the complexity of these interconnected dimensions holds the potential to reveal not only greater understanding into mobility preferences and current EV deployment; but general consumer behavior across a broader spectrum of technologies, uses, and purchasing decisions.

Acknowledgments

The authors are appreciative to the Danish Council for Independent Research (DFF) Sapere Aude Grant 4182-00033B "Societal Implications of a Vehicle-to-Grid Transition in Northern Europe," which has supported elements of the work reported here. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of the DFF. The first author was supported in part by the Engineering Research Center Program of the National Science Foundation (NSF) and the Department of Energy in The United States under NSF Award Number EEC-1041877 and the CURENT Industry Partnership Program. The authors thank Dr. Xiaojing Xu for her suggestions on data analysis.

References

[1] International Energy Agency, "Global EV Outlook 2018," 2018.
[2] International Energy Agency, "Global EV Outlook 2019," 2019.
[3] E. A. F. Observatory, "Europe," 2018. .
[4] J. Kester, L. Noel, G. Zarazua de Rubens, and B. K. Sovacool, "Promoting Vehicle to Grid (V2G) in the Nordic region: Expert advice on policy mechanisms for accelerated diffusion," *Energy Policy*, vol. 116, no. October 2017, pp. 422–432, 2018.
[5] International Energy Agency, "Global EV Outlook 2017: Two million and counting," *IEA Publ.*, pp. 1–71, 2017.
[6] Z. Y. She, Q. Sun, J. J. Ma, and B. C. Xie, "What are the barriers to widespread adoption of battery electric vehicles? A survey of public perception in Tianjin, China," *Transp. Policy*, vol. 56, no. February, pp. 29–40, 2017.
[7] L. Noel, G. Zarazua de Rubens, J. Kester, and B. K. Sovacool, *Vehicle-to-Grid: A Sociotechnical Transition Beyond Electric Mobility*. 2019. Springer International Publishing.
[8] X. Hu, H. Wang, and X. Tang, "Cyber-Physical Control for Energy-Saving Vehicle Following With Connectivity," *IEEE Trans. Ind. Electron.*, vol. 64, no. 11, pp. 8578–8587, 2017.
[9] X. Tang, D. Zhang, T. Liu, A. Khajepour, and H. Wang, "Research on the energy control of a dual-motor hybrid vehicle during engine start-stop process," *Energy Vol.*, pp. 1–1322, 2019.
[10] N. S. Pearre and H. Ribberink, "Review of research on V2X technologies, strategies, and operations," *Renew. Sustain. Energy Rev.*, vol. 105, pp. 61–70, 2019.
[11] Y. Zheng, S. Niu, Y. Shang, Z. Shao, and L. Jian, "Integrating plug-in electric vehicles into power grids: A comprehensive review on power interaction mode, scheduling methodology and mathematical foundation," *Renew. Sustain. Energy Rev.*, vol. 112, pp. 429–439, 2019.
[12] B. K. Sovacool, L. Noel, J. Axsen, and W. Kempton, "The neglected social dimensions to a vehicle-to-grid (V2G) transition: A critical and systematic review," *Environ. Res. Lett.*, vol. 13, no. 1, 2018.
[13] J. Axsen, S. Goldberg, and J. Bailey, "How might potential future plug-in electric vehicle buyers differ from current 'Pioneer' owners?," *Transp. Res. Part D Transp. Environ.*, vol. 47, pp. 357–370, 2016.
[14] S. Hardman, E. Shiu, and R. Steinberger-wilckens, "Comparing high-end and low-end early adopters of battery electric vehicles," *Transp. Res. Part A*, vol. 88, pp. 40–57, 2016.
[15] A. Wolf and S. Seebauer, "Technology adoption of electric bicycles: A survey among early adopters," *Transp. Res. Part A Policy Pract.*, vol. 69, pp. 196–211, 2014.
[16] I. Vassileva and J. Campillo, "Adoption barriers for electric vehicles: Experiences from early adopters in Sweden," *Energy*, vol. 120, pp. 632–641, 2017.
[17] G. Zarazua de Rubens, "Who will buy EVs after early adopters? Using machine learning to identify EV mainstream buyers and their characteristics," *J. Power Prod.*, 2018.
[18] L. Noel, A. P. Carrone, A. F. Jensen, G. Zarazua de Rubens, J. Kester, and B. K. Sovacool, "Willingness to Pay for Electric Vehicles and Vehicle-to-Grid Applications: A Nordic Choice Experiment," *Energy Econ.*, vol. Submitted, 2018.
[19] Nissan, "ALL-NEW NISSAN LEAF," 2018. [Online]. Available: https://www.nissanusa.com/vehicles/electric-cars/leaf.html?dcp=psn.58700002284570040&gclid=CjwKCAjw8uLcBRACEiwAaL6MSYOlAJE31uxtChuiG7YP24YTtktR-KugP866k5hiyAvCcuybfZ2xIhoC_UkQAvD_BwE&gclsrc=aw.ds&dclid=CPfdh7Ontt0C

Fc0SgQodiTUF1Q. [Accessed: 12-Sep-2018].
[20] M. Ferguson, M. Mohamed, C. D. Higgins, and E. Abotalebi, "How open are Canadian households to electric vehicles ? A national latent class choice analysis with willingness-to-pay and metropolitan characterization," *Transp. Res. Part D*, vol. 58, no. December 2017, pp. 208–224, 2018.
[21] X. Yang, W. Jin, H. Jiang, Q. Xie, W. Shen, and W. Han, "Car ownership policies in China: Preferences of residents and influence on the choice of electric cars," *Transp. Policy*, vol. 58, no. February, pp. 62–71, 2017.
[22] McKinsey, "Electric vehicles in Europe," *Evolution (N. Y).*, no. April, p. 21, 2014.
[23] B. Nykvist and M. Nilsson, "The EV paradox - A multilevel study of why Stockholm is not a leader in electric vehicles," *Environ. Innov. Soc. Transitions*, vol. 14, pp. 26–44, 2015.
[24] M. Büchs and S. V. Schnepf, "Who emits most? Associations between socio-economic factors and UK households' home energy, transport, indirect and total CO2 emissions," *Ecol. Econ.*, vol. 90, pp. 114–123, 2013.
[25] J. Axsen and K. S. Kurani, "Developing sustainability-oriented values: Insights from households in a trial of plug-in hybrid electric vehicles," *Glob. Environ. Chang.*, vol. 23, no. 1, pp. 70–80, 2013.
[26] A. Asadinejad, M. G. Varzaneh, K. Tomsovic, C. F. Chen, and R. Sawhney, "Residential customers elasticity estimation and clustering based on their contribution at incentive based demand response," in *IEEE Power and Energy Society General Meeting*, 2016, vol. 2016-November.
[27] M. Coffman, P. Bernstein, and S. Wee, "Factors Affecting EV Adoption : A Literature Review and EV Forecast for Hawaii," no. April 2015, pp. 1–36, 2015.
[28] P. Weldon, P. Morrissey, and M. O'Mahony, "Long-term cost of ownership comparative analysis between electric vehicles and internal combustion engine vehicles," *Sustain. Cities Soc.*, vol. 39, pp. 578–591, May 2018.
[29] M. D. Galus, M. Zima, and G. Andersson, "On integration of plug-in hybrid electric vehicles into existing power system structures," *Energy Policy*, vol. 38, no. 11, pp. 6736–6745, 2010.
[30] M. Wolsink, "The research agenda on social acceptance of distributed generation in smart grids: Renewable as common pool resources," *Renew. Sustain. Energy Rev.*, vol. 16, no. 1, pp. 822–835, 2012.
[31] Deloitte Development LLC, "Global Automotive Consumer Study Exploring consumers' mobility choices and transportation decisions," 2014.
[32] J. Kester, L. Noel, G. Zarazua de Rubens, and B. K. Sovacool, "Policy mechanisms to accelerate electric vehicle adoption: A qualitative review from the Nordic region," *Renew. Sustain. Energy Rev.*, vol. 94, pp. 719–731, Oct. 2018.
[33] J. M. Dargay, "Determinants of car ownership in rural and urban areas: A pseudo-panel analysis," *Transp. Res. Part E Logist. Transp. Rev.*, vol. 38, no. 5, pp. 351–366, 2002.
[34] G. de Jong, J. Fox, A. Daly, M. Pieters, and R. Smit, "Comparison of car ownership models," *Transp. Rev.*, vol. 24, no. 4, pp. 379–408, 2004.
[35] N. Jakobsson, T. Gnann, P. Plötz, F. Sprei, and S. Karlsson, "Are multi-car households better suited for battery electric vehicles ? – Driving patterns and economics in Sweden and Germany," *Transp. Res. Part C*, vol. 65, pp. 1–15, 2016.
[36] R. F. Abenoza, O. Cats, and Y. O. Susilo, "Travel satisfaction with public transport: Determinants, user classes, regional disparities and their evolution," *Transp. Res. Part A Policy Pract.*, vol. 95, pp. 64–84, 2017.
[37] A. Ensslen, A.-G. Paetz, S. Babrowski, P. Jochem, and W. Fichtner, "On the Road to an Electric Mobility Mass Market—How Can Early Adopters be Characterized?," pp. 21–51, 2015.

[38] P. D. Larson, J. Viáfara, R. V. Parsons, and A. Elias, "Consumer attitudes about electric cars: Pricing analysis and policy implications," *Transp. Res. Part A Policy Pract.*, vol. 69, pp. 299–314, 2015.
[39] A. F. Jensen, E. Cherchi, and S. L. Mabit, "On the stability of preferences and attitudes before and after experiencing an electric vehicle," *Transp. Res. Part D Transp. Environ.*, vol. 25, pp. 24–32, Dec. 2013.
[40] M. Ryghaug and M. Toftaker, "A Transformative Practice? Meaning, Competence, and Material Aspects of Driving Electric Cars in Norway," *Nat. Cult.*, vol. 9, no. 2, Jan. 2014.
[41] O. Hagman, "Mobilizing meanings of mobility: Car users' constructions of the goods and bads of car use," *Transp. Res. Part D Transp. Environ.*, vol. 8, no. 1, pp. 1–9, 2003.
[42] O. Hagman, "Driving Pleasure: A key concept in Swedish car culture," *Mobilities*, vol. 5, no. 1, pp. 25–39, 2010.
[43] M. Kukova, C. Diels, and H. Kharouf, "Do we really know which vehicle attributes are important for customers ?," *Conf. Pap.*, no. September, 2016.
[44] T. Laurence and P. C. Macharis, "Clean Vehicle Research Consumer Behaviour for Purchasing Cars Task 1 . 4," 2008.
[45] WEVE, "What drives consumers along the automotive purchase journey ?," 2017.
[46] A. Nayum, C. A. Klöckner, and M. Mehmetoglu, "Comparison of socio-psychological characteristics of conventional and battery electric car buyers," *Travel Behav. Soc.*, vol. 3, pp. 8–20, 2016.
[47] J. D. Adler, P. B. Mirchandani, G. Xue, and M. Xia, "The Electric Vehicle Shortest-Walk Problem With Battery Exchanges," *Networks Spat. Econ.*, vol. 16, no. 1, pp. 155–173, 2016.
[48] J. Dong, C. Liu, and Z. Lin, "Charging infrastructure planning for promoting battery electric vehicles: An activity-based approach using multiday travel data," *Transp. Res. Part C Emerg. Technol.*, vol. 38, pp. 44–55, 2014.
[49] S. Habib, M. Kamran, and U. Rashid, "Impact analysis of vehicle-to-grid technology and charging strategies of electric vehicles on distribution networks - A review," *J. Power Sources*, vol. 277, pp. 205–214, 2015.
[50] T. Franke and J. F. Krems, "What drives range preferences in electric vehicle users?," *Transp. Policy*, vol. 30, pp. 56–62, 2013.
[51] L. Noel, G. Zarazua de Rubens, B. K. Sovacool, and J. Kester, "Fear and loathing of electric vehicles: The reactionary rhetoric of range anxiety," *Energy Res. Soc. Sci.*, vol. 48, pp. 96–107, Feb. 2019.
[52] G. Pasaoglu, D. Fiorello, A. Martino, L. Zani, A. Zubaryeva, and C. Thiel, "Travel patterns and the potential use of electric cars - Results from a direct survey in six European countries," *Technol. Forecast. Soc. Change*, vol. 87, pp. 51–59, 2014.
[53] M. Khan and K. M. Kockelman, "Predicting the market potential of plug-in electric vehicles using multiday GPS data," *Energy Policy*, vol. 46, pp. 225–233, 2012.
[54] O. Egbue and S. Long, "Barriers to widespread adoption of electric vehicles: An analysis of consumer attitudes and perceptions," *Energy Policy*, vol. 48, no. 2012, pp. 717–729, 2012.
[55] A. Le Duigou, Y. Guan, and Y. Amalric, "On the competitiveness of electric driving in France: Impact of driving patterns," *Renew. Sustain. Energy Rev.*, vol. 37, pp. 348–359, 2014.
[56] N. Rauh, T. Franke, and J. F. Krems, "Understanding the impact of electric vehicle driving experience on range anxiety," *Hum. Factors*, vol. 57, no. 1, pp. 177–187, 2015.
[57] J. S. Krupa *et al.*, "Analysis of a consumer survey on plug-in hybrid electric vehicles," *Transp. Res. Part A Policy Pract.*, vol. 64, pp. 14–31, 2014.
[58] M. Friman, L. Larhult, and T. Gärling, "An analysis of soft transport policy measures implemented in Sweden to reduce private car use," *Transportation (Amst).*, vol. 40, no. 1,

pp. 109–129, 2013.
[59] F. Mwasilu, J. J. Justo, E. K. Kim, T. D. Do, and J. W. Jung, "Electric vehicles and smart grid interaction: A review on vehicle to grid and renewable energy sources integration," *Renew. Sustain. Energy Rev.*, vol. 34, pp. 501–516, 2014.
[60] J. Neubauer and E. Wood, "The impact of range anxiety and home, workplace, and public charging infrastructure on simulated battery electric vehicle lifetime utility," *J. Power Sources*, vol. 257, pp. 12–20, 2014.
[61] M. Bockarjova and L. Steg, "Can Protection Motivation Theory predict pro-environmental behavior? Explaining the adoption of electric vehicles in the Netherlands," *Glob. Environ. Chang.*, vol. 28, no. 1, pp. 276–288, 2014.
[62] K. Degirmenci and M. H. Breitner, "Consumer purchase intentions for electric vehicles: Is green more important than price and range?," *Transp. Res. Part D Transp. Environ.*, vol. 51, pp. 250–260, 2017.
[63] A. M. Peters, E. van der Werff, and L. Steg, "Beyond purchasing: Electric vehicle adoption motivation and consistent sustainable energy behaviour in The Netherlands," *Energy Res. Soc. Sci.*, vol. 39, no. October 2017, pp. 234–247, 2018.
[64] J. Axsen and K. S. Kurani, "Hybrid, plug-in hybrid, or electric-What do car buyers want?," *Energy Policy*, vol. 61, pp. 532–543, 2013.
[65] D. McCoy and S. Lyons, "Consumer preferences and the influence of networks in electric vehicle diffusion: An agent-based microsimulation in Ireland," *Energy Res. Soc. Sci.*, vol. 3, no. C, pp. 89–101, 2014.
[66] E. Graham-Rowe *et al.*, "Mainstream consumers driving plug-in battery-electric and plug-in hybrid electric cars: A qualitative analysis of responses and evaluations," *Transp. Res. Part A Policy Pract.*, vol. 46, no. 1, pp. 140–153, Jan. 2012.
[67] M. E. Kahn, "Do greens drive Hummers or hybrids? Environmental ideology as a determinant of consumer choice," *J. Environ. Econ. Manage.*, vol. 54, no. 2, pp. 129–145, 2007.
[68] G. Schuitema, J. Anable, S. Skippon, and N. Kinnear, "The role of instrumental, hedonic and symbolic attributes in the intention to adopt electric vehicles," *Transp. Res. Part A Policy Pract.*, vol. 48, pp. 39–49, Feb. 2013.
[69] B. K. Sovacool and P. L. Blyth, "Environmental attitudes in the green state of Denmark : Implications for energy democracy , low carbon transitions , and energy literacy," *Environ. Sci. Policy*, vol. 54, pp. 304–315, 2015.
[70] P. Wells and D. Xenias, "From 'freedom of the open road' to 'cocooning': Understanding resistance to change in personal private automobility," *Environ. Innov. Soc. Transitions*, vol. 16, pp. 106–119, 2015.
[71] N. Melton, J. Axsen, and D. Sperling, "Moving beyond alternative fuel hype to decarbonize transportation," *Nat. Energy*, vol. 1, no. 3, p. 16013, 2016.
[72] J. Cohen and P. Cohen, *Applied Multiple Regression/Correlation Analysis for the Behavioral Sciences*, 2nd ed. Hillsdale, NJ: Lawrence Erlbaum Associates, 1983.
[73] J. V Petrocelli, B. H. Cohen, and A. Wampold, "Problems and Possible Remedies," *Meas. Eval. Couns. Dev.*, vol. 36, no. April, pp. 9–22, 2003.
[74] B. E. Wampold and R. D. Freund, "Use of Multiple Regression in Counseling Psychology Research: A Flexible Data-Analytic Strategy," *J. Couns. Psychol.*, vol. 34, no. 4, pp. 372–382, 1987.
[75] D. J. Benjamin *et al.*, "Redefine statistical significance," *Nat. Hum. Behav.*, vol. 2, no. 1, pp. 6–10, 2018.
[76] J. Gareth, W. Daniela, H. Trevor, and R. Tibshirani, *An Introduction to Statistical Learning with Applications in R*. New York: Springer, New York, NY, 2013.
[77] N. Roberts and J. Thatcher, "Conceptualizing and testing formative constructs," *ACM SIGMIS Database*, vol. 40, no. 3, p. 9, 2009.

[78] C. fei Chen, X. Xu, and L. Arpan, “Between the technology acceptance model and sustainable energy technology acceptance model: Investigating smart meter acceptance in the United States,” *Energy Res. Soc. Sci.*, vol. 25, pp. 93–104, 2017.
[79] H. Du, D. Liu, B. K. Sovacool, Y. Wang, S. Ma, and R. Y. M. Li, “Who buys New Energy Vehicles in China? Assessing social-psychological predictors of purchasing awareness, intention, and policy,” *Transp. Res. Part F Traffic Psychol. Behav.*, vol. 58, pp. 56–69, 2018.
[80] C. A. Klöckner, A. Nayum, and M. Mehmetoglu, “Positive and negative spillover effects from electric car purchase to car use,” *Transp. Res. Part D*, vol. 21, pp. 32–38, 2013.
[81] “Ethics and Privacy_Chen.”
[82] W. A. Boland, M. Brucks, and J. H. Nielsen, “The Attribute Carryover Effect: What the ‘Runner-Up’ Option Tells Us about Consumer Choice Processes,” *J. Consum. Res.*, vol. 38, no. 5, pp. 872–885, 2012.
[83] J. Després, S. Mima, A. Kitous, P. Criqui, N. Hadjsaid, and I. Noirot, “Storage as a flexibility option in power systems with high shares of variable renewable energy sources: a POLES-based analysis,” *Energy Econ.*, vol. 64, pp. 638–650, 2017.